IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

Applicants:	Ira Cohen et al.	§	Art Unit:	2153
Serial No.:	10/026,061	§		
		§	Examiner:	Yasin M. Barqadle
Filed:	December 18, 2001	§		
For:	Adapting Bayesian Network Parameters On-Line in a Dynamic Environment	§	Atty. Dkt. No.:	10006656-1 (HPC.0573US)

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Commissioner for Patents
P.O. Box 1450
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APPEAL BRIEF PURSUANT TO 37 C.F.R § 41.37

Sir:

The final rejection of claims 11, 12, 15-23, and 26-29 is hereby appealed.

I. REAL PARTY IN INTEREST

The real party in interest is Hewlett-Packard Development Company, L.P.

II. RELATED APPEALS AND INTERFERENCES

None.

III. STATUS OF THE CLAIMS

Claims 11, 12, 15-23, and 26-29 have been finally rejected and are the subject of this appeal. Claims 1-10, 13, 14, 24, and 25 have been cancelled.

Date of Deposit: August 20, 2008

I hereby certify under 37 CFR 1.8(a) that this correspondence is being transmitted electronically to the U.S. Patent Office on the date indicated above.

Ginger Yount

Ginger Yount

IV. STATUS OF AMENDMENTS

No amendment after the final rejection, dated March 30, 2008, has been filed.

V. SUMMARY OF THE CLAIMED SUBJECT MATTER

The following provides a concise explanation of the subject matter defined in each of the independent claims involved in the appeal, referring to the specification by page and line number and to the drawings by reference characters, as required by 37 C.F.R. § 41.37(c)(1)(v). Each element of the claims is identified by a corresponding reference to the specification and drawings where applicable. Note that the citation to passages in the specification and drawings for each claim element does not imply that the limitations from the specification and drawings should be read into the corresponding claim element.

Independent claim 11 recites a method for adapting a Bayesian network, comprising:

> generating (Fig. 2:102) a set of parameters for the Bayesian network in response to a set of past observation data such that the Bayesian network models an environment (Spec., p. 5, lines 12-13);
>
> obtaining a set of present observation data from the environment (Spec., p. 6, lines 1-4; p. 14, lines 1-5);
>
> determining (Fig. 4:114) an estimate of the parameters in response to the present observation data (Spec., p. 14, lines 1-5);
>
> adapting (Fig. 4:116, 118) a learning rate for the parameters such that the learning rate responds to changes in the environment indicated in the present observation data by increasing the learning rate when an error between the estimate and a mean value of the parameters is relatively large and decreasing the learning rate when convergences is reached between the estimate and the mean value of the parameters (Spec., p. 14, lines 7-21);
>
> updating (Fig. 2:104) the parameters in response to the present observation data using the learning rate (Spec., p. 5, line 33-p. 6, line 3); and
>
> using the Bayesian network to model the environment and diagnose problems or predict events in the environment (Spec., p. 1, lines 12-23).

Independent claim 21 recites a hardware system, comprising:

> environment that generates a set of present observation data (Spec., p. 6, lines 1-4; p. 14, lines 1-5);
>
> Bayesian network (Fig. 1:52) that performs automated reasoning for the environment in response to the present observation data (Spec., p. 5, lines 5-11);
>
> adapter (Fig. 1:56) that obtains the present observation data from the environment and that determines an estimate of a set of parameters for the Bayesian network in response to the present observation data by adapting a learning rate for the parameters to respond to changes in the environment by increasing the learning rate when an error between the estimate and a mean value of the parameters is relatively large and decreasing the learning rate when convergences is reached between the estimate and the mean value of the parameters, wherein the Bayesian network models the environment and diagnoses problems or predicts events in the environment (Spec., p. 1, lines 12-23; p. 5, line 33-p. 6, line 3; p. 14, lines 7-21).

VI. GROUNDS OF REJECTION TO BE REVIEWED ON APPEAL

A. Claims 11, 12, 15, 20-23, and 26-29 Rejected Under 35 U.S.C. § 101.

B. Claims 11, 12, 15, 16, 20-23, and 26 Rejected Under 35 U.S.C. § 102(b) as Anticipated by Eric Bauer et al., "In Proceedings of the Thirteenth Annual Conference on Uncertainty in Artificial Intelligence (UAI-97) (Bauer).

C. Claims 17-19 and 27-29 Rejected Under 35 U.S.C. § 103(a) as Unpatentable Over Bauer in View of U.S. Patent Application Publication No. 2003/0018494 (Bronstein).

VII. ARGUMENT

The claims do not stand or fall together. Instead, Appellant presents separate arguments for various independent and dependent claims. Each of these arguments is separately argued below and presented with separate headings and sub-headings as required by 37 C.F.R. § 41.37(c)(1)(vii).

A. Claims 11, 12, 15, 20-23, and 26-29 Rejected Under 35 U.S.C. § 101.

1. Claims 11, 12, 15, 20.

Independent claim 11 was rejected as being "an abstract idea rather than a practical application of the idea." 3/20/2008 Office Action at 4. The Examiner argued that independent claim 11 does not "provide a useful, concrete, and tangible result." *Id.* at 4-5.

Appellant respectfully disagrees, since independent claim 11 is directed to a specific practical application, namely "using the Bayesian network to model the environment and diagnose problems or predict events in the environment."

There are three categories of subject matter that are unpatentable: laws of nature, natural phenomena, and abstract ideas. *State Street Bank & Trust Company v Signature Financial Group, Inc.*, 149 F.3d 1368, 1373, 47 U.S.P.Q.2d 1596 (Fed. Cir. 1998). "Unpatentable mathematical algorithms are identifiable by showing they are merely abstract ideas constituting disembodied concepts or truths that are not 'useful.'" *Id.* As noted by *State Street Bank*, "to be patentable an algorithm must be applied in a 'useful' way. *Id.* A mathematical algorithm thus is considered statutory subject matter if it produces a useful, concrete, and tangible result. *Id. State Street Bank* held that the transformation of data representing discrete dollar amounts by a machine through a series of mathematical calculations into a final share price constitutes a practical application of a mathematical algorithm, formula, or calculation, because it produces a useful, concrete, tangible result. *Id.*

In another case, a claimed process that applied Boolean algebra to data to determine the value of a PIC indicator was held to constitute statutory subject matter. *AT&T Corp. v. Excel Communications, Inc.*, 172 F.3d 1352, 1358, 50 U.S.P.Q.2d 1447 (Fed. Cir. 1999).

In this case, claim 11 specifically recites that the Bayesian network is used to model the environment and to diagnose problems or predict events in the environment, where a set of parameters for the Bayesian network is generated in response to a set of past observation data, and where parameters of the Bayesian network are estimated in response to present observation data. A person of ordinary skill in the art would have understood the usefulness of performing updates of parameters of a Bayesian network that is used to model the environment as recited in claim 11. As examples, Bayesian networks can be used to model biological systems, including humans and animals, electrical systems, mechanism systems, software systems, business transaction systems, and so forth. Specification, p. 1, lines 14-17.

As set forth by the M.P.E.P., to determine whether a claimed invention covers a practical application in performing a § 101 analysis, the claim has to be reviewed to determine if it produces a useful, tangible, and concrete result. M.P.E.P. § 2106 (8th ed., Rev. 6), at 2100-11. A concrete result is present if the process has a result that can be substantially repeatable. *Id.* at 2100-12. Independent claim 11 recites a method that is clearly repeatable. Therefore, the concrete result requirement of the practical application analysis is satisfied.

It is also noted that claim 1 provides a tangible result, since claim 1 recites a method for adapting a Bayesian network that is used to model an environment and diagnose problems or predict events in the environment.

Finally, the useful result requirement for the practical application analysis is satisfied since claim 1 satisfies the utility requirement of § 101. As stated by the M.P.E.P., an invention is useful if it satisfies the utility requirement of § 101. As provided in M.P.E.P. § 2107, the guidelines for examination of applications for compliance with the utility requirement specify that the Examiner is to review the claims and the supporting written description to determine if

the applicant has asserted for the claimed invention any specific and substantial utility that is credible. M.P.E.P. § 2107, at 2100-20.

As recited in claim 11, the Bayesian network of claim 11 is used to model an environment and diagnose problems or specific events in the environment. As explained by the Specification, in some examples, Bayesian networks can be used to model biological systems, including humans and animals, electrical systems, mechanical systems, software systems, business transaction systems, and so forth.

In view of the foregoing, it is clear that claim 11 and its dependent claims are directed to statutory subject matter. In view of the foregoing, reversal of the § 101 rejection of the above claims is respectfully requested.

2. Claims 21-23, 26.

Independent claim 21 was rejected under § 101 for two reasons. First, the Examiner argued that claim 21 is directed to a "program per se" and is therefore non-statutory. 3/20/2008 Office Action at 4. Moreover, the Examiner argued that claim 20 is directed to an abstract idea and does not provide a useful, concrete, and tangible result. *Id.* at 4-5.

For reasons similar to those stated above with respect to claim 11, it is respectfully submitted that claim 21 is directed to a practical application, as claim 21 specifically recites that the Bayesian network models the environment and diagnoses problems or predicts events in the environment. Moreover, as explained above, the Specification provides various examples of environments that a Bayesian network can model.

In response to the Examiner's allegation that claim 21 is a program *per se*, that assertion is clearly incorrect. Claim 21 recites a **hardware** system that includes the elements claim 21. The Examiner argued that "claiming a hardware system in the preamble without showing a

physical hardware in the claim limitations do not change the scope of the claims being non-statutory." 3/20/2008 Office Action at 2. Ignoring a limitation in a claim in rendering the § 101 rejection constitutes clear legal error. The fact that the preamble of claim 21 recites a "hardware" system clearly takes claim 21 out of the realm of being a program *per se*. A program *per se* refers to software that is recited merely as a program listing that is not part of any physical structure. In contrast, claim 21 recites a "hardware system," which necessarily means that it cannot possibly constitute a program *per se*.

In view of the foregoing, reversal of the § 101 rejection of the above claims is respectfully requested.

3. Claims 27-29.

Dependent claims 27-29 further recite that the environment that is modeled by the Bayesian network is an email system, e-commerce system, or database system. Such recitation provides additional practical application in these claims.

Therefore, reversal of the § 101 rejection of the above claims is respectfully requested.

B. Claims 11, 12, 15, 16, 20-23, and 26 Rejected Under 35 U.S.C. § 102(b) as Anticipated by Eric Bauer et al., "In Proceedings of the Thirteenth Annual Conference on Uncertainty in Artificial Intelligence (UAI-97) (Bauer).

1. Claims 11, 12, 15, 16, 20.

Bauer clearly does not disclose at least the following element of claim 11:

adapting a learning rate for the parameters such that the learning rate responds to changes in the environment indicated in the present observation data by **increasing** the learning rate when an **error between the estimate and a mean value** of the parameters is relatively large and **decreasing** the learning rate when convergences is reached between the **estimate and the mean value** of the parameters;

Paragraph 64 on page 10 of Bauer (as identified by the Examiner in an annotated version of Bauer) states that the learning rate η can be adapted over time, "based on the number of examples seen so far ...." However, even though Bauer mentions the adaptation of the learning rate, η, there is absolutely nothing in Bauer to even remotely hint at **increasing** the learning rate when an **error between the estimate and a <u>mean</u> value of the parameters** is relatively large, and **decreasing** the learning rate when convergences is reached between **the estimate and the <u>mean</u> value of the parameters**. In the response to arguments section of the final rejection, the Examiner made the following assertion:

> Baur for example teaches "Our update rule for the t 2 distance results in a family of update rules with varying learning rates n. This family, which we denote EM(n), includes the standard EM algorithm [6, 8] as the special case EM(1). From the relative entropy distance, we derive an analogous family of multiplicative update rules which, following [12, 10], we call EG(n). In particular, we show in Section 4 that, while 1 is the largest value of n for which convergence to a local maximum is guaranteed, some value n~ which is bigger than 1 provides the optimal convergence rate. More precisely, for any (local or global) maximum of the likelihood function, there is a value n~>1 and a neighborhood around the local maximum, such that EM(n) provides the fastest convergence (of any EM(n) algorithm) to the maximum in that neighborhood." (Page 2 paragraph 3-4). The fact the one value appears to work well it is does not mean the learning rate does not increase or decrease as argued by the Applicant. It just says that some value bigger than 1 provides an optimal convergence. See convergence property section on page 5 and page 10 paragraphs 1-4. See also err graphs in fig. 3 top of page 9).

3/20/2008 Office Action at 3.

The Examiner did not explain how the quoted language above teaches the subject matter of claim 11. More specifically, there is nothing in the quoted language to disclose increasing the learning rate when an error between the estimate and a mean value of the parameters is relatively large, and decreasing the learning rate when convergences is reached between the estimate and the mean value of the parameters.

In view of the foregoing, it is respectfully submitted that claim 11 and its dependent claims are clearly allowable over Bauer.

Reversal of the final rejection of the above claims is respectfully requested.

2. Claims 21-23, 26.

Independent claim 21 is also not anticipated by Bauer, which fails to disclose adapting a learning rate for parameters of a Bayesian network to respond to changes in the environment by **increasing** the learning rate when **an error between the estimate and a <u>mean</u> value** of the parameters is relatively large and **decreasing** the learning rate when the convergences is reached between the **estimate and the <u>mean</u> value** of the parameters.

Therefore, claim 21 and its dependent claims are also allowable over Bauer.

Reversal of the final rejection of the above claims is respectfully requested.

C. Claims 17-19 and 27-29 Rejected Under 35 U.S.C. § 103(a) as Unpatentable Over Bauer in View of U.S. Patent Application Publication No. 2003/0018494 (Bronstein).

1. Claims 17-19, 27-29.

In view of the defective rejection of base claims over Bauer, it is respectfully submitted that the obviousness rejection of dependent claims 17-19 and 27-29 over Bauer and Bronstein is also defective.

Reversal of the final rejection of the above claims is respectfully requested.

CONCLUSION

In view of the foregoing, reversal of all final rejections and allowance of all pending claims is respectfully requested.

Respectfully submitted,

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VIII. APPENDIX OF APPEALED CLAIMS

The claims on appeal are:

11. A method for adapting a Bayesian network, comprising:

generating a set of parameters for the Bayesian network in response to a set of past observation data such that the Bayesian network models an environment;

obtaining a set of present observation data from the environment;

determining an estimate of the parameters in response to the present observation data;

adapting a learning rate for the parameters such that the learning rate responds to changes in the environment indicated in the present observation data by increasing the learning rate when an error between the estimate and a mean value of the parameters is relatively large and decreasing the learning rate when convergences is reached between the estimate and the mean value of the parameters;

updating the parameters in response to the present observation data using the learning rate; and

using the Bayesian network to model the environment and diagnose problems or predict events in the environment.

12. The method of claim 11, wherein adapting comprises adapting a different learning rate for each parameter of the Bayesian network.

15. The method of claim 11, wherein a subset of values in the present observation data is unavailable when updating.

16. The method of claim 11, wherein the environment is an online environment.

17. The method of claim 16, wherein the online environment is an email system.

18. The method of claim 16, wherein the online environment is an e-commerce system.

19. The method of claim 16, wherein the online environment is a database system.

20. The method of claim 11, wherein updating comprises determining an initial set of the parameters and then updating the parameters in response to the present observation data using the learning rate.

21. A hardware system, comprising:

environment that generates a set of present observation data;

Bayesian network that performs automated reasoning for the environment in response to the present observation data;

adapter that obtains the present observation data from the environment and that determines an estimate of a set of parameters for the Bayesian network in response to the present observation data by adapting a learning rate for the parameters to respond to changes in the environment by increasing the learning rate when an error between the estimate and a mean value of the parameters is relatively large and decreasing the learning rate when convergences is reached between the estimate and the mean value of the parameters, wherein the Bayesian network models the environment and diagnoses problems or predicts events in the environment.

22. The hardware system of claim 21, wherein the adapter uses a different learning rate for each parameter of the Bayesian network.

23. The hardware system of claim 21, wherein the adapter determines the parameters by determining an initial set of the parameters and then updating the parameters in response to the present observation data using the learning rate.

26. The hardware system of claim 21, wherein a subset of values in the present observation data is unavailable.

27. The hardware system of claim 21, wherein the environment is an email system.

28. The hardware system of claim 21, wherein the environment is an e-commerce system.

29. The hardware system of claim 21, wherein the environment is a database system.

IX. EVIDENCE APPENDIX

None.

X. RELATED PROCEEDINGS APPENDIX

None.